Does overtime work contribute to the gender earnings gap? Evidence from The Netherlands

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Abstract

The increasing participation of women in both education and the labour market, as well as the consequent rise in their work experience have driven the narrowing of the gap in earnings among women and men. Although the literature examining this convergence has come a long way in the last decades, there are a few insufficiently examined factors that potentially contribute to the gap. This paper combines the traditional view proposed by Labour Economics with the most contemporaneous analysis offered by Personnel Economics to examine the contribution that work hour schedules may have on the monthly earnings gap. Particularly, the focus is on overtime work. It tests the hypotheses as to whether overtime work explains part of the gender gap and if current wage gaps can be explained by overtime in the past. The results point to a positive and significant contribution of total overtime work in both the Oaxaca – Blinder and the pooled decompositions, and even after correcting for selection bias. While only the contribution of past overtime is significant in the Oaxaca – Blinder decomposition, both current and two-year lagged overtime contributions are so in the pooled decomposition.

Keywords: wage gap, monthly earnings, overtime work, working hours, gender, Oaxaca – Blinder, pooled, Personnel Economics

Classification: MSc Thesis

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1 Introduction

The increasing participation of women in both education and the labour market, together with the consequent rise in their work experience have motivated the narrowing of the gap in earnings among women and men. This major convergence has been extensively studied by the branch of the economic literature examining gender differences in pay. This literature has come a long way in the last decades. However, only half of the story is told as it does not explain the gap that persists. The question may arise: Where do we go from here? There are two possible paths. On the one hand, we could argue that no explanation to the persistent gender gap exists other than wage discrimination. On the other hand, there might be under-explored factors that potentially contribute to the gender wage gap. In fact, Boll et al. (2016) defend the existence of a promising and an innovative field of research. Work hour schedules and practices such as overtime work might serve as a good starting point for this analysis.

Before digging deep into those undeveloped aspects it is worth to summarize what we already know. Most of the studies on this topic have based their analysis on the famous Human Capital Theory. Its main takeaway is that one's expected lifetime work history motivates training acquisition which fosters earnings potential. The more years a person works, the higher the value of the human capital investment is and the more likely it is to harvest higher earnings (Polachek, 2004). Women anticipating maternity and the posterior career interruption are less likely to invest in education and job training as their expected return to education is lower (Golding and Polacheck, 1987). This theory successfully explained the part of the gender gap which is motivated by gender differences in human capital investment. However, nowadays women have caught up with men in terms of education, career prospects and labour force participation. As a result, women's productivity has increased to the men's level. At this point, the Human Capital Theory is no longer useful to explain the remaining gender gap as there are (almost) no human capital differences among genders. Goldin (2014) suggests shifting to Personnel Economics to explain why the gender gap remains open. The focus should be now on the selection, matching and sorting processes.

Particularly, the explanation could be related to the theory of equalizing differences or to models of asymmetric information. The former defends the existence of wage differentials to adjust for the total pecuniary and nonpecuniary advantages (or disadvantages) among jobs and among workers themselves (Rosen, 1986). Lower than average wages are necessary to attract labour when the working conditions offered are favourable (e.g. part-time work or other kind of flexible work schedules). On the contrary, employers imposing unfavourable working conditions (e.g inflexible work schedules or shift work) must pay premiums to appeal workers. As women are more likely to experience work interruptions or to enjoy part-time schedules, this theory offers an explanation on why the gap remains open[1]. Yet, other research has proposed a slightly different explanation. Work schedules, particularly working hours, can signal some workers characteristics without changes in productivity. For instance, working longer hours would serve as a signal of commitment, loyalty and willingness to work hard and learn, which would potentially increase pay or the likelihood of promotion. Just as before, this would lower women's wages as they are less likely to work over hours.

Either theory, with or without information symmetry, highlights the weight that work hour schedules have in the pay gap. This paper focusses on work flexibility aiming at shedding some more light on the importance of working hours on the earnings differential. Particularly, the focus is on overtime work, i.e. when working hours exceed the contracted working hours. Overtime can potentially raise wages according to both theories of equalizing differences and signalling. Either way, the question thus arises as to whether overtime work (partly) explains why the wage differential among genders persist.

Additionally, understanding the potential compensation benefits of working overtime, both current and forward looking, is important. Working overtime is a widespread practice nowadays, especially on the corporate and financial job spheres. Workers may be expected to work overtime at the beginning of their career in order to advance to top ranked positions in the nearby future (Cortes, 2015). In other words, workers "invest" time to work overtime to enhance their career prospects (Bell & Hart, 1999). Hence, a second and complementary question is raised: Can current wage gaps be explained by differences in overtime in the past?

Aiming at approaching both research questions, this paper uses data from the LISS panel. The focus is on The Netherlands. This country presents an hourly wage gap which is almost equal to the European average according to the Report on Equality conducted by Eurostat in 2017. Particularly, the hourly wage gap in the Netherlands stood at

[1] Becker (1985) was the first one arguing that household and childcare responsibilities induce married women to reduce both their work hour schedules and their incentives to invest in human capital accumulation in order to effectively balance family and work. This, in turn, results in lower wages to married women relative to men.

approximately 16% in 2014 while the European average was 16.4% in the same year (See Figure 1.A. in the Appendix). However, the average monthly wage of Dutch men in 2015 is notably higher than the Dutch female average (2,967 versus 1,783), suggesting a much broader gap in terms of monthly earnings[2].Even though, there are some differences in terms of magnitude of the pay gap across countries, the roots of the problem are similar among the developed economies. Hence, concerns regarding external validity are reduced.

I use data on monthly earnings from 2016 and data on contractual and actual hours worked to construct measures of overtime work. To this purpose, the panel dimension of the LISS data set is used to obtain information on overtime for the years 2014, 2015 and 2016. Regarding the estimation method, I use the traditional Oaxaca – Blinder decomposition to study the explanatory power of overtime. This approach is supplemented by a pooled decomposition which overcomes the main drawback of the traditional approach, namely the random selection of the wage structure.

The remainder of this paper is structured as follows. Section 2 provides an overview of the current direction of the gender gap literature. Section 3 describes the data. Section 4 presents the estimation method used to answer the research questions. In Section 5 the results of the analysis are displayed. Section 6 finally provides some concluding remarks and discusses avenues for future research.

2 Background Literature

As previously mentioned there is an overwhelming body of literature about the gender pay gap. The purpose of this section is not to summarize all of that work but rather to underline the current direction of this literature and specifically the research which is relevant to my analysis.

Recent literature, such as by Blau & Kahn (2016), brings to the table the limitations of human capital accumulation and discrimination as explanations for the persistent gender differences in pay. During the 1980s, a grand gender convergence in earnings took place. Both the improvements in women's human capital accumulations and the decline in the unexplained portion of the gap were responsible. In the 1990s the convergence slowed down due to the lower decline of the unexplained portion of the gap[3]. Nowadays,

[2] https://www.statista.com/statistics/537993/average-monthly-wage-in-the-netherlands-by-gender/
[3] See Blau & Kahn (2007) for a deeper description in gender gap trends.

the gap in earnings persists. Productivity characteristics still explain part of the pay gap but their weight is decreasing. The unexplained portion is still considerable. However, it is hard to believe that the latter is entirely due to discrimination against women. Blau & Kahn (2007) emphasize that unmeasured productivity levels, qualifications and non-wage related job aspects might account for part of the residual.

Researchers start to offer different explanations for the gender differential in pay. Some argue the existence of psychological divergences across genders, for instance in reactions towards risk, competition or negotiation[4]. Women have been proven to be more risk averse, less competitive and to have weaker negotiation skills (under some circumstances) than their male counterparts in the field. Whether this holds in the labour market is still an open question. Yet, if the importance of these psychological attributes is proven to be large, the lower wage of women would have its roots in history, biology or even culture, and it would be less likely to be eliminated in the near future.

Gendered segregation in employment is often given as an explanation for the wage differential as well. Among the dimensions that employment differences can arise, occupational segregation is the most important. Although there has been an improvement in this respect, Blau & Kahn. (2016) find that occupational differences account for one third of the wage differential in The United States in 2010. Also in North America Petersen & Morgan (1995) find that segregation by occupation surpasses within-job wage discrimination (unequal pay for an equal job) and establishment segregation in explaining gender differences in wage.

Working time cannot be excluded from the catalog of potential explanations either. Particularly, many researches point to the large penalties that women have to face when interrupting their work supply during and/or after maternity. Budig & England (2001) find a wage penalty of approximately 7 percentage points per child, being larger for married women. Boll et al. (2016) underline the negative weight that part-time schedules have on the gender gap. On the other extreme, some have focused on the excessive prize granted to those who overwork or work overtime. Goldin (2014) reaches the conclusion that in certain occupations, mostly those on the corporate and financial world, monthly gains and working hours are not linearly related. The more hours on the job, the higher the chance to be rewarded. The exorbitant reward linked to large working days harms

[4] For a detailed review of recent evidence regarding these topics see Bertrand (2010).

women as they value flexibility more than men do. Based on the results, she argues that the residual differences in pay can be then interpreted as wage differentials.

A small but growing body of literature examines the potential benefits of overtime. Anger (2003) using data from Germany finds a positive although weak correlation between overtime and the likelihood of getting promoted or a pay increase. Interestingly, Anger (2008) estimates a positive signalling value of unpaid overtime by applying a difference-in-differences research design. Subjects working overtime according to all industry thresholds serve as a control group. The treatment is integrated by those who work overtime in some, but not all the industries. Estimation results suggest that unpaid overtime increases monthly earnings by 10-17% in East Germany. Further, a few authors shed light, either directly or indirectly, on the potential role of overtime in explaining wage differentials which are not caused by differences in worker's productivity. Cortes et al. (2015) focus on the demand for long working hours and explore the causal link between the latter and the gender wage gap for high educated employees. They exploit a plausible exogenous intercity variation in low-skilled immigrant flows as an instrument to eliminate endogeneity concerns due to the lack of exogenous variation in the returns to work long hours. They argue that the variation in low-skilled immigrant flows, which affects the females' costs of supplying longer hours of work, does not affect the gender wage gap other than through the costs of working longer hours. They find that low-skilled immigration narrows both the gender gap in supplying long work hours and Cha & Weeden (2014) study the importance of overtime on changes in the wage gap using data from the Current Population Survey (CPS). They implement an alternative decomposition technique developed by Juhn, Murphy and Pierce (1991) which is commonly refer to as JPM decomposition. As such they analyse whether the overtime contribution to the gender gap comes from the increasing returns of overtime work and/or from changes in the gender supply of overwork. Their results suggest that increasing returns associated with overtime work together with its rising popularity have slowed down the narrowing of the gender gap.

This paper adds to the previous literature on the gender gap in two aspects. First, its focus is on The Netherlands instead of the U.S.A as it is the case in the majority of the previous studies. This allows to validate preceding results and contributes to reduce external validity concerns. Second and most significantly, this paper complements the modest literature investigating the importance that overtime work has on explaining the gender gap. The novelty comes from the consideration of both current and prior overtime conditions to accurately account for the return of working overtime.

3 Data

Aiming to approach both research questions, I make use of data of the LISS (Longitudinal Internet Studies for the Social sciences) panel performed across The Netherlands from 2007 until 2016. Administered by CentERdata (Tilburg University, The Netherlands), this panel is the most important component of the Measurement and Experimentation in the Social Sciences (MESS) project. It is a representative sample of 7000 Dutch individuals from 4500 households who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population registered. Households that could not otherwise participate are provided with a computer and Internet connection. Regarding data collection, two principal elements of the LISS panel can be differentiated. On the one hand, background characteristics such as gender, educational level or marital status are updated on a monthly basis. On the other hand, the core studies, covering a large variety of domains including work, education, income and time use, are collected once a year[5].

For my analysis information from both the background variables and the core study of work and schooling is used, mainly from the last wave. My principal variables of interest are wage and overtime. I use gross monthly individual income to account for wage (in)equality. This entails a turning point from previous studies which measure wage as earnings per hour. While differences in hourly wages describe gender dissimilarities in human capital investments and industry and occupational choices (Goldin 2014), monthly earnings depict those differences as well as gender disparities in working hours and overtime work. Thus, this alternative measure offers the examination of the gap in compensations from the perspective of Personnel Economics. It concedes the analysis of the benefits of working hours and of the current and forward benefits of working overtime. Moreover, a second reason exists to use gross monthly earnings. The LISS panel does not provide information on hourly wages which would have to be calculated applying a rule of thumb that equally rewards every working hour. This linear compensation with respect to time is not necessarily the case and less regarding lagged overtime work[6].

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[5] More information about the LISS panel can be found at: www.lissdata.nl .
[6] Working overtime now can increase future wages in a non-linear basis.

To gather information on whether the subject has worked overtime I use the answers of two questions from the 2016/15/14 waves: “How many hours per week do you actually work on average in your job?” and “How many hours per week are you employed in your job, according to your employment contract?”. These answers are exploited to construct two different overtime variables. The first overtime variable results from the difference between the first and the second questions. The second variable is the percentage of overtime[7]. Both measures are advantageous as they control for the plausible mismatch in the definition of overtime in each occupation. For instance, to work overtime in a corporate profession generally requires more hours than in health-related occupations. Also, these measures exploit both the extensive margin and the relative weight of overtime, respectively. These definitions are thus a step forward from previous literature which uses the rule of thumb of 50 or more hours per week as the lower bound of overtime work and therefore studies its intensive margin.

The raw sample is susceptible to some restrictions. All non-employed individuals, and those with zero individual gross monthly income and with missing values in one of the variables considered are excluded. Further, I restrict my analysis to employees between 25 and 65 years old to control for outliers. Subjects younger than 25 years old do not normally have full-time and career related jobs as they are likely to be enrolled in full-time education. On the other extreme, individuals older than 65 years may be near retirement. Those employees with contracts which specify 0 hours per week are not considered as they might distort the analysis. Those subjects are “on-call” employees, meaning that they only get to work when called upon. Two further restrictions are imposed to reduce the heterogeneity of the sample: employees with less than twelve contracted working hours per week and farm workers are dropped from the analysis. By considering only those with more than 12 contracted working hours per week, I am only studying subjects with a certain degree of labour market commitment. Farm workers are left outside of the analysis due to difficulties in disentangle income from capital or in kind income (Blau & Kahn, 2016). On top of this, only those present in the core study of work and schooling in the years 2016, 2015 and 2014 are considered in order to account for

[7] $\%\ of\ Overtime = \frac{Actual\ working\frac{hours}{week} - Contracted\ working\frac{hours}{week}}{Contracted\ working\frac{hours}{week}}$

current and prior overtime statuses. These restrictions together result in a rather homogeneous sample. The final sample consists then on 1,133 observations[8].

Figure 1 offers an analysis of the density distribution of male and female monthly earnings. Both distributions have a positive skew. Yet, differences are noticeable at first sight. Firstly, the male gross monthly distribution lies everywhere to the right of the female one. Women are underrepresented in the upper tails of the wage distribution and males have higher monthly earnings. Secondly, the peak of the female distribution is higher and sharper. The personal monthly income of females is more concentrated around their mode than the one of males. The male earnings show more dispersion

Figure 1. Kernel Density for monthly wages by gender

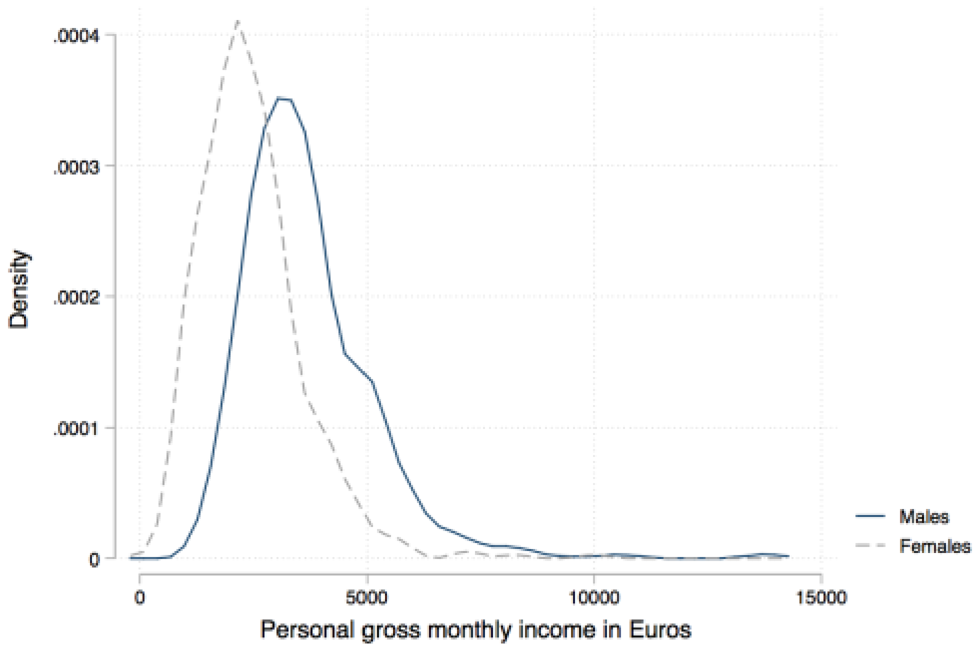


Table 1 contains the descriptive statistics of the variables considered in the analysis[9]. Importantly, both marital status and number of children in the household are not included

[8] The ninth wave of the Core Study of Working and Schooling (year 2016) is distributed to 6,640 individuals. Only 5,832 of those respond (87.8%) and 5,601 effectively complete the survey (Source: www.lissdata.nl). By keeping only workers present in the three consecutive years and dropping those with missing values in one of the variables of interest the sample decreases from 5,832 to 2,751 observations. By considering only workers between 25 and 65 years old the sample size is reduced by 1,589 more observations. Finally, dropping workers with less than 12 contracted hours/week and those in agrarian occupations lowers the number of observations to 1,133.

[9] For descriptive purposes, the quadratic of experience is not reported in the summary statistics. Yet, it is considered in the analysis to model the potential non-linear relationship between earnings and experience. The natural log of monthly earnings is also omitted from the table for ease of the reading.

as covariates due to endogeneity concerns. Generally, being an active worker and, particularly, being an overtime worker might alter the decision to get married or have children. Still, they are contained in Table 1 as they provide valuable information about the sample and are used later on to control for selection bias.

Table 1. Summary statistics

	Female	Male	Total
Main variables			
Gross monthly income			
Mean	2451.41	3676.69	3129.71
Standard deviation	(1142.97)	(1448.97)	(1454.42)
$Weekly\ Overtime_{2016}$			
Mean	1.73	2.96	2.41
Standard deviation	(3.28)	(4.62)	(4.12)
$Weekly\ Overtime_{2015}$			
Mean	1.96	3.20	2.64
Standard deviation	(3.27)	(5.25)	(4.52)
$Weekly\ Overtime_{2014}$			
Mean	1.82	3.13	2.56
Standard deviation	(3.21)	(5.23)	(5.49)
$\%\ Overtime_{2016}$			
Mean	0.060	0.078	0.070
Standard deviation	(0.12)	(0.12)	(0.12)
$\%\ Overtime_{2015}$			
Mean	0.067	0.094	0.082
Standard deviation	(0.11)	(0.26)	(0.21)
$\%\ Overtime_{2014}$			
Mean	0.063	0.087	0.076
Standard deviation	(0.11)	(0.20)	(0.17)
Human capital and job controls			
Level of education:			
Primary school	0.006	0.011	0.009
Intermediate secondary	0.134	0.131	0.132
Higher secondary	0.083	0.072	0.077
Intermediate vocational	0.298	0.309	0.305
Higher vocational	0.346	0.319	0.331
University	0.132	0.158	0.147
Years of Experience (1)			
Mean	33.44	34.73	34.15
Standard deviation	(11.34)	(10.76)	(11.04)
Contracted hours/week			
Mean	29.06	37.63	33.82
Standard deviation	(7.45)	(3.97)	(7.17)
Company ownership: % type			
Private	0.480	0.678	0.590
Public/ semi-public	0.520	0.322	0.410
Sector: % type			
Forestry, fishery and mining	0.002	0.016	0.010
Industrial production	0.047	0.176	0.119
Utilities production, distribution and/or trade	0.004	0.022	0.014
Construction	0.024	0.067	0.049
Retail trade	0.065	0.069	0.067
Transport, storage and communication	0.014	0.070	0.045
Financial	0.048	0.054	0.051
Business services	0.055	0.080	0.069
Government services and public administration	0.093	0.158	0.129
Education	0.111	0.065	0.086

Healthcare and welfare	0.383	0.075	0.213
Other	0.154	0.145	0.149
Profession [(2)]: % type			
High skilled blue collar	0.020	0.110	0.070
Low skilled blue collar	0.040	0.099	0.072
High skilled white collar	0.134	0.263	0.206
Low skilled white collar	0.806	0.528	0.652
Years of job tenure			
Mean	14.05	15.54	14.87
Standard deviation	(10.72)	(11.65)	(11.27)
Demographic controls			
Female: % type			
Female			0.447
Male			0.553
Age			
Mean	46.10	47.43	46.84
Standard deviation	(10.89)	(10.38)	(10.62)
# of children in the household			
Mean	0.929	0.936	0.933
Standard deviation	(1.03)	(1.13)	(1.12)
Marital status: % type			
Married	0.553	0.590	0.574
Not married[(3)]	0.447	0.410	0.426
Origin: % type			
Dutch	0.861	0.852	0.856
1st generation foreign: western	0.022	0.029	0.026
1st generation foreign: non-western	0.036	0.049	0.043
2nd generation foreign: western	0.057	0.053	0.055
2nd generation foreign: non-western	0.024	0.018	0.020
N	506	627	1,133

Notes: [(1)] Experience is proxied with the formula: $experience = age - years\ in\ (full\ time)\ education$. [(2)] High skilled blue-collar workers are those workers performing skilled and supervisory manual labour (e.g. car mechanic). Low skilled blue-collar workers are those workers performing semi-skilled (e.g. baker or driver) or unskilled manual labour (e.g. packer). High skilled white-collar workers perform high intellectual or independent professions and high management occupations (e.g. manager director, etc.). Low skilled white-collar workers perform intermediate intellectual or independent professions (e.g. teacher or medical nurse), intermediate or commercial occupations (e.g. senior representative) or other intellectual occupation (e.g. shopkeeper or department head). This grouping has been done to keep Table 1 as short as possible. Yet, the econometric analysis considers the eight profession categories of the variable. [(3)] Not married individuals are those who are separated, divorced, widow or have never been married[10].

At first sight, two findings are not surprising. The mean gross monthly income of female employees is notably lower than the mean gross monthly income of their male counterparts and therefore lower than the sample mean. Also women work less overtime hours and present a lower overtime percentage on average. Further, the male average contracted hours per week is greater than the female average. Women are more likely than men to work in public or semi-public companies and to work in both education and healthcare sectors. On the contrary, men representation is higher in the sectors of industrial production, finance, business and government services. More than 85% of the sample are white collar workers. Men have on average 16 years of job tenure and 35 years

[10] Source: www.lissdata.nl .

of experience while women have 14 and 33 years, respectively. Lastly, the average individual in the full sample is 47 years old. Men and women are comparable in terms of number of children, origin and level of education.

Table 1.A in the Appendix encloses the correlations between the independent variables. Regarding the time consistency of overtime, the correlation between prior and current overtime conditions is positive and statistically significant at the 1% level. The same holds for the three overtime percentages. Those employees working overtime one year are likely to do it again in the next years. In other words, the individual time variation in overtime status is low. Interestingly, the correlation between overtime and contracted hours is highly significant and positive[11]. Those workers contracting longer hours are likely to work more overtime hours. Contrary, it negatively correlates with experience[12].

More attention should be paid to overtime per se. Figures 1.A – 4.A in the Appendix grants a preliminary study of the distribution of overtime by gender[13]. Women are mainly condensed in zero hours of overtime per week and the female density decreases in weekly hours of overtime. On the contrary, men are concentrated around 1 to 10 hours of weekly overtime and do not have such a clear decreasing pattern as women do. Finally, it is interesting to look at the demographic differences by gender of overtime and no overtime workers. Table 2 grants this analysis. Notably, overtime workers are more likely to have a university degree. Although no major gender differences are found in terms of age, origin and level of education, male overtime workers are slightly more likely to be married and to have children than their female counterparts. Relatedly, while men are more likely to be married when working overtime, the opposite pattern is found among females. Approximately ten per cent more of no overtime female workers are married in comparison with the female workers who perform overtime. The same is true with regard to the number of children. Male workers labouring overtime have relatively more children than the ones not doing so. For females, the opposite holds. All together this sheds light to the seeming trade-off faced by the feminine labour force: career advancement versus family unit building.

[11] This only holds in the relationship between contracted hours and the extensive margin overtime.

[12] Yet, the negative correlation between experience and the overtime variables is not significant at the conventional levels

[13] Those workers with more than 20 hours of overtime per week are not represented in the Figures 1.A – 4.A to facilitate the exposition.

Table 2. Individual demographic and education characteristics of overtime and non-overtime workers by gender

	Overtime		No Overtime	
	Female	**Male**	**Female**	**Male**
Age				
Mean	45.50	46.87	46.93	48.39
Standard deviation	(11.11)	(10.19)	(10.55)	(10.63)
Marital Status: % type				
Married	0.514	0.592	0.609	0.586
Not married	0.486	0.408	0.392	0.414
# of children in the household: % type				
None	0.548	0.506	0.458	0.535
One child	0.153	0.154	0.184	0.147
Two children	0.204	0.228	0.255	0.237
Three children	0.088	0.096	0.085	0.073
Four children	0.007	0.005	0.009	0.009
Five children	0.000	0.008	0.009	0.000
Six children	0.000	0.003	0.000	0.000
Origin: % type				
Dutch	0.844	0.866	0.887	0.828
1st generation foreign: western	0.034	0.030	0.005	0.026
1st generation foreign: non western	0.027	0.035	0.047	0.073
2nd generation foreign: western	0.061	0.051	0.052	0.056
2nd generation foreign: non western	0.034	0.018	0.009	0.017
Level of education				
Primary school	0.003	0.003	0.009	0.026
Intermediate secondary	0.092	0.076	0.193	0.224
Higher secondary	0.075	0.063	0.094	0.086
Intermediate vocational	0.248	0.286	0.368	0.349
Higher vocational	0.391	0.357	0.283	0.254
University	0.191	0.215	0.052	0.060
Total	294	395	212	232

4 Estimation Method

4.1 The traditional decomposition

The empirical strategy that I choose to answer the research question is clear-cut. Aiming at analysing the relationship between the earnings gender gap and overtime work, I start by implementing a revised version of the Oaxaca and Blinder (1973) decomposition method. This method is the gold standard to estimate the gender wage gap (Kunze, 2008) as it pulls the explained portion of the gap apart from the residual or "wage discrimination" part. Notably, it enables different compensations for male and female productivity characteristics (Weichselbaumer, 2005). The classical approach stays close to the Theory of Human Capital as it only accounts for productive factors such as education or experience. The residual part accounts for the differential in earnings of equally productive males and females. As the productive differences between men and women have declined while the wage gap remains open, I expand the original model by controlling for the available individual measurable characteristics that are likely to further explain the gender gap. Particularly, I control for overtime work. Log wage equations are estimated for individuals i of different gender g ($g = male, female$) at time t ($t = 2016$) using Ordinary Least Squares (OLS),

$$W_{git} = \beta_g X_{git} + \ \delta_g Overtime_{gi,t-n} + \varepsilon_{git} \quad (1)$$

where W_{git} is the log of the individual gross monthly income and X_{git} is a vector of human capital, job and demographic characteristics, usually known as endowments (e.g. level of education, experience, type of job, job tenure, occupation, industry, etc.). As experience is a linear combination of age and years of education, the simultaneous inclusion of both age and experience, and their squares is not possible due to collinearity[14]. I decide to account for experience and its square since they are considered as essential in gender analysis[15]. $Overtime_{gi,t-n}$ measures if the individual i of gender g has worked overtime in the period $t - n$ ($n = 0, \ldots, 2$) and how many overtime hours per week he/she has worked[16], with δ_g a vector estimate of the overtime log wage benefit. Finally, ε_{git} is the residual characterized by the equation,

$$\varepsilon_{git} = v_{gi} + u_{git} \quad (2)$$

where v_{gi} denotes time invariant unobserved individual attributes and u_{git} is a zero mean and constant variance random component.

The reason to include two prior overtime conditions on equation (1) is twofold. Firstly, its inclusion grants the examination of the potential long-run return of overtime. In other words, the estimation of equation (1) allows to test whether working overtime positively relates to future wages. I am able to account for both direct and indirect overtime outcomes. Given sample restrictions, equation (1) only looks backwards two years. That is, adding more overtime lags would dramatically reduce the sample size and therefore the validity of the results. Secondly, those workers who decide to work overtime are likely to present different measured and unmeasured characteristics relative to those who do not. Consequently, whether overtime condition is correlated to those fixed unobserved individual characteristics contained on ε_{git} raises a concern, namely omitted

[14] The correlation between age and experience equals 0.9814 being significant at the 1% level.
[15] The seminal work of Blinder (1973) has been criticized for using age and its square as proxies for work experience. Same age subjects can differ in work experience if they have achieved different educational levels (for a detailed discussion see Rosenzweig et al. (1976)).
[16] When instead the overtime percentage measures are used, $Overtime_{gi,t-n}$ is the percentage of overtime that the individual i of gender g has done in the period $\mathrm{t} - \mathrm{n}$ ($\mathrm{n} = 0, \ldots, 2$).

variable bias. Equation (1) controls for this endogeneity problem by including overtime conditions in the two previous years ($Overtime_{gi,t-1}$ and $Overtime_{gi,t-2}$). Following Hirsch (2005), prior overtime conditions may be an important component of worker's current wage as it reflects part of those unmeasured individual skills.

At this point, a sceptical reader could be wondering why not to use individual fixed effects. A few reasons are to mention here. First and foremost, sample restrictions do not allow their application. Overtime statuses present a high consistency across the years. Secondly, a contemporaneous analysis could potentially underestimate the future returns of working overtime (Cortes & Pan, 2015) and therefore its signalling and behavioural components. Also, overtime differences are likely to arise between jobs while fixed effects only account for within differences. Finally, the main reason behind the inclusion of individual fixed effect in the decomposition would be to drop any bias caused by unobserved individual heterogeneity. Yet, Heitmüller (2005) proofs that including fixed effects in the Oaxaca – Blinder decomposition augments the problem of omitted variables instead of dropping the potential bias[17]. I therefore opt for analysing how current and prior overtime statuses relate to the current gender gap.

After the estimation of equation (1), the Oaxaca-Blinder decomposition of the wage gap follows. The total gap is broken up into an explained part and an unexplained component from the male's perspective[18],

$$\begin{aligned}\bar{W}_m - \bar{W}_f = {} & \hat{\beta}_m\left(\bar{X}_m - \bar{X}_f\right) + \hat{\delta}_m\left(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}\right) \\ & + \bar{X}_m\left(\hat{\beta}_m - \hat{\beta}_f\right) + \overline{Overtime}_{m,t-n}\left(\hat{\delta}_m - \hat{\delta}_f\right) \\ & - \left(\bar{X}_m - \bar{X}_f\right)\left(\hat{\beta}_m - \hat{\beta}_f\right) \\ & - \left(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}\right)\left(\hat{\delta}_m - \hat{\delta}_f\right) \equiv E + U + I\end{aligned} \tag{3}$$

where those variables with upper bars are means, and $\hat{\beta}_g$ and $\hat{\delta}_g$ denote the estimated parameters of Equation (1). The term on the left-hand side, that is the difference in mean logarithmic wages, is the raw wage gap which is decomposed into three parts. The term E is the "explained part" which is accounted for by gender differences in the considered endowments. It is made up of the first two terms: $\hat{\beta}_m\left(\bar{X}_m - \bar{X}_f\right)$ and $\hat{\delta}_m\left(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}\right)$. The term U is the so-called "discrimination effect" which is the sum of $\bar{X}_m\left(\hat{\beta}_m - \hat{\beta}_f\right)$ and $\overline{Overtime}_{m,t-n}\left(\hat{\delta}_m - \hat{\delta}_f\right)$. It accounts for

[17] This critique of the use of individual fixed effects only apply to decompositions such as the Oaxaca – Blinder approach. It should not be generalized to other econometric models.
[18] The mean differences in the endowments are weighted by the male price coefficients.

the differences in wages due to gender disparities in price coefficients. This text however refers to the U term as the unexplained or residual part of the gap. The term discrimination is not appropriate as there might be individual unobserved predictors that are not accounted for in equation (1). Besides, the remaining components form the interaction term denoted by I. It allows for the existence of simultaneous differences in both endowments and coefficients between males and females (Jann, 2008).

4.2 An alternative decomposition

Equation (3) assumes no discrimination against men, neither positive or negative, and completely addresses the wage discrimination towards women (Jann, 2008). Nevertheless, it is plausible that the discrimination against women is accompanied by a positive bias towards men. Further, if the coefficients of the price vector $\hat{\delta}_m$ are large, equation (3) would underestimate the gender difference in overtime behaviour. Thus, some authors have proposed to weight the differences in endowments with the average of both coefficients instead and therefore use a more general decomposition. The pooled decomposition equation is as follows,

$$\begin{aligned}\bar{W}_m - \bar{W}_f = \hat{\beta}^*\left(\bar{X}_m - \bar{X}_f\right) + \hat{\delta}^*\left(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}\right) \\ + \bar{X}_m\left(\hat{\beta}_m - \hat{\beta}^*\right) + \overline{Overtime}_{m,t-n}\left(\hat{\delta}_m - \hat{\delta}^*\right) + \bar{X}_f\left(\hat{\beta}^* - \hat{\beta}_f\right) \\ + \overline{Overtime}_{f,t-n}\left(\hat{\delta}^* - \hat{\delta}_f\right) \equiv E' + U'\end{aligned} \quad (4)$$

where $\hat{\beta}^* = 0.5(\beta_f) + 0.5(\beta_m)$ and $\hat{\delta}^* = 0.5(\delta_f) + 0.5(\delta_m)$. In this specification $E' = \hat{\beta}^*\left(\bar{X}_m - \bar{X}_f\right) + \hat{\delta}^*\left(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}\right)$ and $U' = \bar{X}_m\left(\hat{\beta}_m - \hat{\beta}^*\right) + \overline{Overtime}_{m,t-n}\left(\hat{\delta}_m - \hat{\delta}^*\right) + \bar{X}_f\left(\hat{\beta}^* - \hat{\beta}_f\right) + \overline{Overtime}_{f,t-n}\left(\hat{\delta}^* - \hat{\delta}_f\right)$. Importantly, equation (4) includes a gender component as an extra covariate[19]. Following Jann (2008) and Elder et al. (2010), not including the gender indicator would make equation (4) to suffer from omitted variable bias and to underestimate the residual part of the gap. That is, part of the residual component would reallocate to the explained part of the gap artificially augmenting the explanatory power of the endowments.

Different specifications of equations (3) and (4) are estimated to analyse the contribution that overtime has on the gender wage gap. All together this estimation method allows to address the questions as to whether overtime explains part of the gap

[19] The log wage equations in the pooled model are as follows: $W_{git} = \alpha + \varphi_{0f}F_i + \beta_g X_{git} + \delta_g Overtime_{gi,t-n} + \varepsilon_{git}$ where F_i is a dummy variable that equals to 1 if female and 0 otherwise.

and whether the current wage gap can also be explained by differences in overtime in the past. Particularly, I expect a positive overtime contribution to the gender wage gap. Working overtime can signal non-productive worker attributes such as commitment or loyalty which might positively impact wages. Yet, working overtime requires subjects to have no constraints. Women may face important restrictions, such as maternity or other family responsibilities, which interfere with working overtime. The potential male advantage in overtime condition, both current and prior, is then likely to explain part of the gap.

4.3 Overcoming selection bias

Still, the above analysis ignores an important issue, namely selection bias. Those individuals participating in the labour market may make up a selective group of subjects which are the only ones with access to wage information. Offered wages (expressed with equation (1)) are not the same as observed wages, and the latter are likely to be affected by subject's unobserved characteristics and choices about whether or not to take part in the labour market.

As such, the offered wage function (equation (1)) should be prudently distinguished from the observed wage equation (Reimers, 1983) denoted as,

$$E\left(W_{git} \middle| X_{git}, in\ sample\right) = \beta_g X_{git} + \delta_g Overtime_{gi,t-n} + E\left(\varepsilon_{git} \middle| in\ sample\right) \qquad (5)$$

with $E\left(\varepsilon_{git} \middle| in\ sample\right) \neq 0$ due to non-random participation in the labour market. Thus, neither the estimates of the wage equation, nor the expected wage are unbiased.

The most straightforward approach to deal with this problem is the Heckman (Heckit) two-step correction. The first stage consists on the estimation of the probability to participate in the labour market, i.e. the probability of having a paid work. Being $Paid\ work_{gi} = \gamma_g H_{gi} + u_{gi}$ the participation equation, the following probit maximum likelihood model is estimated,

$$\Pr(Paid\ work = yes)_{gi} = \Pr\left(u_{gi} > -\gamma_g H_{gi}\right) = \Phi(\gamma_g H_{gi}) + u_{gi} \qquad \text{(Stage 1)}$$

where H_{gi} is a vector of determinants of participation in paid work. γ_g is the associated parameter vector and Φ is the standard normal of the cumulative distribution function (Neuman & Oaxaca, 2004).

Finding the appropriate exclusion restrictions is key for the validity of this approach (Puhani, 2000). In other words, the correct specification of Stage 1 requires to find variables that determine the probability to participate in paid work without directly affecting the outcome equation. The most commonly used participation determinants in the literature are age and its square, number of children and civil status[20]. However, both age and its square are not likely to fulfill the assumption. Therefore, I run the probit model using three consistent determinants of paid work participation: number of children, civil status and position within the household[21].

In the second stage, the wage equation of the employed individuals is estimated with OLS,

$$(W_{git} | Paid\ work_{gi} = yes) = \beta_g X_{gi} + \delta_g Overtime_{gi,t-n} + \theta_g \lambda_{gi} + \epsilon_{git} \quad \text{(Stage 2)}$$

where λ_{gi} is the inverse of the Mill's ratio calculated from the probit model (Stage 1), θ_g is the covariance between the errors of the probit and the wage equations and ϵ_{git} is the normally distributed and zero mean error term.

Given equation (6), the decomposition corrected for selection bias looks as follows,

$$\begin{aligned}(\bar{W}_m - \bar{W}_f) = {} & \hat{\beta}_m(\bar{X}_m - \bar{X}_f) + \hat{\delta}_m(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}) \\ & + \bar{X}_m(\hat{\beta}_m - \hat{\beta}_f) + \overline{Overtime}_{m,t-n}(\hat{\delta}_m - \hat{\delta}_f) \\ & - (\bar{X}_m - \bar{X}_f)(\hat{\beta}_m - \hat{\beta}_f) \\ & - (\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}})(\hat{\delta}_m - \hat{\delta}_f) + (\widehat{\lambda^m}\hat{\theta}_m \\ & - \widehat{\lambda^f}\hat{\theta}_f)\end{aligned} \quad (6)$$

where the first five terms are those of equation (3) and the last one is the selectivity correction term. Equation (6) does not assign gender differences in selection components neither to the unexplained part, nor to the explained part of the gap or to the interaction term (Neuman & Oaxaca, 2004). There is no consensus on how this last term should be tackled. The easiest approach consists on deducting the selection effect from the raw differential and then apply the decomposition to the corrected differential (Jann, 2008),

$$\begin{aligned}(\bar{W}_m - \bar{W}_f) - (\widehat{\lambda^m}\hat{\theta}_m - \widehat{\lambda^f}\hat{\theta}_f) \\ = {} & \hat{\beta}_m(\bar{X}_m - \bar{X}_f) + \hat{\delta}_m(\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}}) \\ & + \bar{X}_m(\hat{\beta}_m - \hat{\beta}_f) + \overline{Overtime}_{m,t-n}(\hat{\delta}_m - \hat{\delta}_f) \\ & - (\bar{X}_m - \bar{X}_f)(\hat{\beta}_m - \hat{\beta}_f) \\ & - (\overline{Overtime_{m,t-n}} - \overline{Overtime_{f,t-n}})(\hat{\delta}_m - \hat{\delta}_f)\end{aligned} \quad (7)$$

[20] See Reimers (1983), Heinze et al. (2003), Wooldridge (2006), and Jann (2008).
[21] Position within the household is a categorical variable having two categories: household head, wedded partner and other. This variable is gathered from the background data set.

Caution should be taken in the interpretation of equation (7). It decomposes the corrected wage differential into the endowment, the residual and the interaction effect, but the corrected wage differential does not necessarily equal the observed wage differential (Neuman & Oaxaca, 2004).

5 Results

5.1 The Blinder – Oaxaca and the Pooled decompositions

The results of both the Blinder – Oaxaca and the pooled decompositions executed for the full sample by the estimation of equations (3) and (4), respectively, are reported in this section. With the purpose of providing a better picture of the contribution of overtime statuses to the gender gap, three different specifications of equations (3) and (4) are estimated. This "build on" design permits to analyse whether the still unexplained part of the wage gap decreases after accounting for overtime statuses.

Nonetheless, it is informative to step back in the analysis and briefly discuss the outcome results of the estimated log wage equations. This allows to inspect whether the overtime variables and the individual gross monthly income are substitutes or complements. Table 2.A. in the Appendix displays the results of the log wage equations by gender and of the pooled log wage equation. Results of column (1) suggest that a one per cent increase in overtime work rise the monthly wage of women by 1.05% after two years. In the case of men, a significant and positive relationship between wage and overtime is found in the same year in which overtime is performed (column (2)). Thus, the returns of working overtime are directly effective for men but only affect women wages after two years. The estimated outcome of the pooled wage equation suggests a positive and highly significant current and two-year lagged return of overtime[22]

Table 3 shows the results of the Oaxaca – Blinder decomposition. A note of caution should be made before starting with the analysis. The raw gender earnings gap reported along this text is larger than in other studies. The reason is that those previous studies examine the hourly wage gap. This text focusses on the raw monthly wage gap,

[22] Current overtime is statistically and economically significant in the three specifications when excluding past overtime conditions from the regressions. In the female log wage equation, the current overtime coefficient equals 0.0117 with a significance at the 5% level. The male's coefficient is statistically significant at the 1% level and its economic magnitude equals 0.0117. The log price benefit of current overtime is 0.0120 in the pooled equation, with a significance at the 1% level. These slight differences are caused by the strong correlation between the three overtime statuses. The mean of the Variance Inflation Factors (VIF) is less than 10, being the VIF of the three overtime statuses around 2.40. Concerns about multicollinearity are as such reduced.

and therefore contracted hours are not discounted from the differential until I control for them[23].

Column (1.a) includes only human capital and demographic individual characteristics. The predicted means of wages in logarithmic scale are 7.6977 for females and 8.1427 for males, which translates into a total earnings gap of 0.4450. That is, there is a gender difference in monthly wages of the 56.05%. Together human capital controls and origin only account for 3.26% of the gap (0.0145/0.4450). Yet, this contribution is not statistically significant. The estimated unexplained part of the gap suggests that female wages would increase by 53.49% if their endowments were weighted by the males' coefficients. This unexplained part is disproportionately large as only human capital and origin controls are included. All together this shows that no significant male advantage exists in terms of human capital characteristics and origin nowadays. Other researchers, as Goldin (2014) and Blau & Kahn (2016), also evidence that the human capital contribution to the gap has been squeezed out.

Column (2.a) controls for job characteristics as well as for the latter endowments. Gender differences in human capital, origin and job characteristics account for more than four fifths of the gap[24]. Particularly, differences in contracted hours between men and women explain most of the wage difference. If women worked the same hours as men, the wage gap in euros would increase by 36.51%. This is not surprising as part time schedules are very popular in The Netherlands, especially among women. The 76.6% of Dutch women worked part time in 2014 (Eurostat). Interestingly, the estimated coefficient of the mean gender differences in private sector participation is negative. The conditional compensation in private companies is higher than in public or semi-public companies[25]. Although, it is not statistically significant.

[23] Goldin (2014) or Fortin et al. (2017) estimates of monthly and annual earnings gaps, respectively, are similar in magnitude to the one reported along this text.
[24] Precisely, they account for the 81.87% of the gap (0.3643/0.4450)
[25] Boll et al. (2016) find the same result.

Table 3. Blinder – Oaxaca decomposition of the monthly earnings gap, 2016

	(1.a)			(2.a)			(3.a)		
Predicted wages of males	8.1427***			8.1427***			8.1427***		
Predicted wages of females	7.6977***			7.6977***			7.6977***		
	Log scale		% points (€)	Log scale		% points (€)	Log scale		% points (€)
Total earnings gap	0.4450	***	56.05	0.4450	***	56.05	0.4450	***	56.05
	(0.026)		(0 .041)	(0.026)		(0 .041)	(0.026)		(0.041)
Explained part (E)	0.0145		1.46	0.3643	***	43.95	0.3782	***	45.96
	(0.017)		(0.018)	(0.029)		(0.042)	(0.029)		(0.043)
Unexplained part (U)	0.4285	***	53.49	0.2135	***	23.80	0.2135	***	23.80
	(0.023)		(0.035)	(0.036)		(0.044)	(0.036)		(0.045)
Interaction part (I)	0.0020		0.20	-0.1328	***	-12.44	-0.1467	***	-13.65
	(0.011)		(0.011)	(0.037)		(0.033)	(0.038)		(0.032)
Contribution to explained part:									
∑ Human capital controls	**0.0143**		**1.44**	**0.0195**	*	**1.97**	**0.0187**	*	**1.88**
	(0.017)		(0.018)	(0.010)		(0.011)	(0.010)		(0.010)
Education variables	0.0077		0.77	0.0066		0.66	0.0062		0.62
	(0.018)		(0 .018)	(0.011)		(0.011)	(0.010)		(0.010)
Experience	0.0073		0.73	0 .0328	*	3.33	0.0304		3.09
	(0.012)		(0 .012)	(0.019)		(0.020)	(0.018)		(0.019)
Experience squared	-0.0007		-0.07	-0.0199		-1.97	-0.0179		-1.78
	(0.010)		(0.010)	(0.014)		(0.014)	(0.013)		(0.013)
∑ Demographic controls	**0.0003**		**0.03**	**-0.0012**		**-0.12**	**-0.0010**		**-0.10**
	(0.003)		(0.003)	(0.002)		(0.002)	(0.002)		(0.002)
Origin	0.0003		0.03	-0.0012		-0.12	-0.0010		-0.010
	(0.003)		(0.003)	(0.002)		(0.002)	(0 .002)		(0.002)
∑ Job controls				**0.3460**	***	**41.35**	**0.3384**	***	**40.26**
				(0.026)		(0.036)	(0.025)		(0.035)
Contracted hours				0.3112	***	36.51	0.3042	***	35.56
				(0.023)		(0.031)	(0.022)		(0.030)
Private company				-0.0080		-0.80	-0.0096		-0.95
				(0.007)		(0.006)	(0.006)		(0.006)
Sector variables				0.0274	*	2.78	0.0294	**	2.99
				(0.015)		(0.015)	(0.014)		(0.015)
Profession variables				0.0116		1.17	0.0105		1.06
				(0.012)		(0.012)	(0.011)		(0.012)
Job tenure				0.0038		0.38	0.0037		0.38
				(0.003)		(0.003)	(0.003)		(0.003)
∑ Overtime statuses							**0.0221**	***	**2.24**
							(0.008)		(0.008)
$Weekly\ Overtime_{2016}$							0.0085		0.85
							(0.008)		(0.008)
$Weekly\ Overtime_{2015}$							-0.00003		-0.003
							(0.007)		(0.007)
$Weekly\ Overtime_{2014}$							0.0137	*	1.38
							(0.007)		(0.007)
Contribution to unexplained part:									
∑ Human capital controls	**0.4738**	***	**60.61**	**0.0652**		**6.74**	**0.0653**		**7.41**
	(0.166)		(0.266)	(0.140)		(0.151)	(0.141)		(0.153)
∑ Demographic controls	**0.0812**	*	**8.45**	**-0.0129**		**-1.28**	**-0.0115**		**-1.28**
	(0.043)		(0.047)	(0.035)		(0.035)	(0.035)		(0.035)
∑ Job controls				**-0.6478**	***	**-47.68**	**-0.6305**	***	**-47.08**
				(0.149)		(0.078)	(0.150)		(0.079)
∑ Overtime statuses							-0.0080		-0.79
							(0.011)		(0.011)
$Weekly\ Overtime_{2016}$							0.0024		0.24
							(0.013)		(0.013)
$Weekly\ Overtime_{2015}$							0.0002		0.02
							(0.013)		(0.013)
$Weekly\ Overtime_{2014}$							-0.0106		-1.06
							(0.011)		(0.011)
N	1,133			1,133			1,133		

Note: Entries are gender differences in endowments multiplied by the correlative male coefficients. Robust standard errors in parentheses. The deviation contrast transformation to dummy variables sets is applied to make the contribution of a categorical predictor to the unexplained part of the decomposition independent of the base category choice. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Besides, accounting for job characteristics drops the residual part of the gap from 0.4285 to 0.2135 log points[26]. The negative interaction term favours women.

On top of this, Column (3.a) adds overtime conditions. Interestingly, the inclusion of current and lagged overtime statuses increases the explained part of the gap from 0.3643 to 0.3782. Even though the economic magnitude of this change is not large, it is statistically significant at the 1% level. If women's total overtime levels were adjusted to the men's level, women earnings would significantly rise by 2.24%. Importantly, only the contribution of overtime in 2014 is statistically significant. These results proof that overtime work is a stronger argument to explain the wage gap than the one of gender differences in human capital investments.

All the considered endowments together account for approximately the 85% of the gap (0.3782/0.4450). Regarding the unexplained portion, results suggest higher returns to job endowments for women. Neither of the three overtime statuses present a significant contribution to the unexplained portion of the gap. There is no evidence of different returns to overtime by gender.

Notwithstanding, as already discussed in the previous section, these results and conclusions are drawn from the estimation of equation (3) which weights the differences in endowments with the male's coefficients. If instead the female's coefficients would have been applied, the proportion of the gender gap explained by differences in endowments would have been unlike. It seems appropriate to use a different price structure, namely "non-discriminatory" price vector. Table 4 reports the estimation results for the full sample of the pooled decomposition which is based on equation (4). As before, each column's specification builds upon the last.

The predicted mean wages in log points and therefore the predicted wage gap reported on Table 4 are the same as before. Also, similar qualitative results as in column (1. a.) are found in column (1.b), which further defends the insignificant contribution to the gap that human capital controls and origin have alone nowadays.

[26] This still substantial unexplained part might be due to omitted variables. For instance, the LISS panel does not provide individual information about academic grades, actual years of work experience or company's size.

Table 4. Pooled decomposition of the monthly earnings gap, 2016

	(1.b)			(2.b)			(3.b)		
Predicted wages of males	8.1427***			8.1427***			8.1427***		
Predicted wages of females	7.6977***			7.6977***			7.6977***		
	Log scale		% points (€)	Log scale		% points (€)	Log scale		% points (€)
Total earnings gap	0.4450	***	56.05	0.4450	***	56.05	0.4450	***	56.05
	(0.026)		(0.041)	(0.026)		(0.041)	(0.026)		(0.041)
Explained part (E)	0.0138		1.39	0.3410	***	40.63	0.3466	***	41.42
	(0.014)		(0.014)	(0.026)		(0.037)	(0.026)		(0.037)
Unexplained part (U)	0.4312	***	53.91	0.1040	***	10.96	0.0984	***	10.35
	(0.022)		(0.034)	(0.021)		(0.023)	(0.021)		(0.023)
Contribution to explained part:									
∑ Human capital controls	**0.0176**		**1.77**	**0.0200**	*	**2.02**	**0.0190**	*	**1.92**
	(0.014)		(0.014)	(0.010)		(0.011)	(0.010)		(0.010)
Education variables	0.0059		0.59	0.0057		0.57	0.0053		0.53
	(0.015)		(0.015)	(0.011)		(0.011)	(0.010)		(0.010)
Experience	0.0169		1.71	0.0275	*	2.79	0.0258	*	2.62
	(0.011)		(0.011)	(0.015)		(0.016)	(0.014)		(0.015)
Experience squared	-0.0052		-0.52	-0.0132		-1.31	-0.0122		-1.21
	(0.007)		(0.007)	(0.009)		(0.009)	(0.008)		(0.008)
∑ Demographic controls	**-0.0037**		**-0.37**	**-0.0029**		**-0.29**	**-0.0025**		**-0.25**
	(0.003)		(0.003)	(0.002)		(0.002)	(0.002)		(0.002)
Origin	-0.0037		-0.37	-0.0029		-0.29	-0.0025		-0.25
	(0.003)		(0.003)	(0.002)		(0.002)	(0.002)		(0.002)
∑ Job controls				**0.3239**	***	**38.24**	**0.3120**	***	**36.62**
				(0.022)		(0.031)	(0.022)		(0.030)
Contracted hours				0.2816	***	32.53	0.2754	***	31.70
				(0.020)		(0.027)	(0.020)		(0.026)
Private company				-0.0050		-0.50	-0.0063		-0.63
				(0.005)		(0.005)	(0.005)		(0.005)
Sector variables				0.0352	***	3.59	0.0347	***	3.53
				(0.010)		(0.011)	(0.011)		(0.011)
Profession variables				0.0094		0.95	0.0051		0.51
				(0.010)		(0.010)	(0.009)		(0.009)
Job tenure				0.0026		0.26	0.0031	*	0.31
				(0.002)		(0.002)	(0.002)		(0.002)
∑ Overtime statuses							**0.0180**	***	**1.82**
							(0.005)		(0.005)
$Weekly\ Overtime_{2016}$							0.0091	**	0.92
							(0.004)		(0.005)
$Weekly\ Overtime_{2015}$							0.0012		0.12
							(0.004)		(0.004)
$Weekly\ Overtime_{2014}$							0.0077	**	0.77
							(0.004)		(0.004)
Contribution to unexplained part:									
∑ Human capital controls	**0.4789**	***	**61.43**	**0.0655**		**6.77**	**0.0653**		**6.74**
	(0.165)		(0.267)	(0.137)		(0.146)	(0.138)		(0.147)
∑ Demographic controls	**0.0788**	*	**8.20**	**-0.0144**		**-1.43**	**-0.0130**		**-1.29**
	(0.043)		(0.046)	(0.034)		(0.034)	(0.034)		(0.033)
∑ Job controls				**-0.7560**	***	**-53.05**	**-0.7425**	***	**-52.41**
				(0.164)		(0.077)	(0.164)		(0.078)
∑ Overtime statuses							**-0.0096**		**-0.95**
							(0.013)		(0.013)
$Weekly\ Overtime_{2016}$							0.0034		0.34
							(0.016)		(0.016)
$Weekly\ Overtime_{2015}$							-0.0009		-0.09
							(0.014)		(0.014)
$Weekly\ Overtime_{2014}$							-0.0122		-1.21
							(0.013)		(0.012)
N	1,133			1,133			1,133		

Note: Entries are gender differences in endowments multiplied by the correlative pooled coefficients. Robust standard errors in parentheses. The deviation contrast transformation to dummy variables sets is applied to make the contribution of a categorical predictor to the unexplained part of the decomposition independent of the base category choice. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Again, adding job controls notably reduces the unexplained portion of the gap and augments the explained one (see column (2.b)). Human capital, origin and job controls explain all together the 76.63% of the gap (0.3410/0.4450). Although contracted hours still contribute the most, experience and sector categories also play a significant explanatory role[27].

The full specification is displayed in column (3.b). Gender differences in human capital, origin, job characteristics and overtime statuses explain the 77.89% of the gap (0.3466/0.4450). That is, if women were comparable to men in all the endowments, their monthly wage would increase by 41.42%. With regard to overtime conditions, they significantly explain 4.05% of the differential (0.0180/0.4450). In this case, current and two-lagged overtime conditions are significant at the 5% level. Accounting for overtime decreases the residual part of the gap from 0.1040 to 0.0984 log points. Although, once again, the contribution of overtime statutes to the unexplained portion is not statistically significant at conventional levels.

Both decompositions arrive at similar qualitative results and show that gender differences in the mean supply of overtime work significantly widens the gender wage gap. Results differ slightly more in quantitative terms. This is due to the application of different price structures. Still, it is worth to devote some lines to explain where the differences in overtime statuses come from. In the Oaxaca – Blinder decomposition only the contribution of overtime in 2014 is statistically significant, while in the pooled decomposition the contribution of the latter and the one of 2016 are so. The price coefficient of 2016 is the highest for men according to the estimation of the males' log wage equation (See Table 2.A. in the Appendix). So that, the Oaxaca – Blinder method underestimate the contribution of overtime in 2016. Importantly, even though the economic magnitude of total overtime is not large[28] in neither of the decompositions, its contribution is not negligible in comparison to other factors.

[27] The positive contribution of sector categories to the gap sustain the notion of sectoral segregation. Females tend to work in sectors with lower pay levels in comparison to those where normally males work.

[28] The Blinder – Oaxaca decomposition and the pooled decomposition estimate a total overtime contribution to the gap of 4.97 % and 4.05%, respectively.

Table 5 presents the results for both the Blinder – Oaxaca and the pooled decompositions with the alternative main independent variables. For the ease of the analysis only the full specification is displayed. Both decompositions arrive to similar quantitative and qualitative results to those of tables 3 and 4 in terms of human capital and demographic controls. The estimated contribution of overtime is lower in both decompositions in comparison with the latter results. If women employees were comparable with their male counterparts in regard to overtime work, their monthly wage would increase by 1.08% and 0.81% according to the Blinder – Oaxaca and the pooled decompositions, respectively.

Table 5. Decomposition of the gender earnings gap with overtime statuses in percentage points, 2016

	Oaxaca-Blinder decomposition			**Pooled decomposition**		
Predicted wages of males	8.1427***			8.1427***		
Predicted wages of females	7.6977***			7.6977***		
	Log scale		% points (€)	Log scale		% points (€)
Total wage gap	0.4450	***	56.05	0.4450	***	56.05
	(0.026)		(0.041)	(0.026)		(0.041)
Explained part (E)	0.3770	***	45.79	0.3470	***	41.48
	(0.029)		(0.041)	(0.026)		(0.037)
Unexplained part (U)	0.2101	***	23.38	0.0980	***	10.30
	(0.037)		(0.046)	(0.021)		(0.023)
Interaction term (I)	-0.1421	***	-13.25			
	(0.038)		(0.033)			
Contribution to explained part:						
$\sum$ **Human capital controls**	**0.0187**	*	**1.89**	**0.0191**	*	**1.93**
	(0.010)		(0.010)	(0.010)		(0.010)
$\sum$ **Demographic controls**	**-0.0011**		**-0.11**	**-0.0026**		**-0.26**
	(0.002)		(0.002)	(0.002)		(0.002)
$\sum$ **Job controls**	**0.3486**	***	**41.70**	**0.3224**	***	**38.04**
	(0.025)		(0.036)	(0.022)		(0.031)
$\sum$ **Overtime percentages**	**0.0108**	**	**1.08**	**0.0081**	**	**0.81**
	(0.005)		(0.005)	(0.004)		(0.004)
$\%\ Weekly\ Overtime_{2016}$	0.0054		0.54	0.0074	**	0.74
	(0.004)		(0.004)	(0.003)		(0.003)
$\%\ Weekly\ Overtime_{2015}$	0.0002		0.02	-0.0014		-0.14
	(0.005)		(0.005)	(0.001)		(0.001)
$\%\ Weekly\ Overtime_{2014}$	0.0052		0.52	0.0021		0.21
	(0.004)		(0.004)	(0.002)		(0.002)
N	1,133			1,133		

Note: Entries are gender differences in endowments multiplied by the correlative male/pooled coefficients. Robust standard errors in parentheses. Deviation contrast transformation to dummy variables sets is applied to make the contribution of a categorical predictor to the unexplained part of the decomposition independent of the base category choice. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

The question thus arises as to why these alternative independent variables do not deal with the same results as the previous ones. One potential reason is that the definition of overtime and its return is different across occupations. In other words, the overtime threshold varies across occupations as its compensation does. For instance, in the corporate and financial occupations where contracted hours are normally high, a given worker to do overtime needs to have worked long hours before. Thus, it is plausible that the (short/long run) return to work one overtime hour is greater than in other professions in which the contracted hours are lower. This turns to be a problem as the overtime percentage variable weights the extensive margin of overtime with contracted hours. Thus, it diminishes the importance of working overtime in those occupations in which overtime potentially grants a higher return. By using this alternative measure, I then underestimate the contribution of overtime to the gap.

5.2 The Heckman correction

A well-known fact in the literature is that the major concern surrounding the estimation of the gender gap is selection bias. This problem affects women more than men as the participation fraction of females in paid work is lower. Thus, a correction is applied to women. I explore the selection issue in Tables 3.A in the Appendix and in Table 6[29]. Regarding the estimation of the participation equation (First Stage in Table 3.A in the Appendix) some findings deserve to be mentioned. The coefficients of one child, two children and four children are positive and statistically significant. Women having one to three children are more likely to participate in the labour market in comparison to those who do not have children. Although this can sound contradictory, it is plausible. Having children involves higher costs within the family unit, which calls for a greater household income[30]. Further, being the wedded partner within the household or occupy a position different than being the head of the household, decreases the probability to participate in the labour market.

In the second part of Table 3.A. in the Appendix the results of the second stage are displayed. The inverse Mills ratio is negative meaning that the unobservables in the selection equation are negatively correlated to those of the outcome equation. Although, it is not statistically significant. Previous results are not likely to be driven by selection bias. However, this is not an absolute truth. Table 6 shows the estimation results of the Oaxaca – Blinder decomposition after applying the Heckman correction. Without the

[29] Table 3.A. in the Appendix displays the first and second stages of the selectivity correction adjustment method.

[30] The descriptive analysis granted by Table 2 in Section 3 shows that more than a half of the no overtime females workers have one to three children.

selectivity correction, the predicted wages of women in log points are 0.037 lower than the Heckman's prediction (7.6977 versus 7.7347). That is, the uncorrected predicted female's wages are somewhat biased downwards. Relatedly, the wage gap is estimated with a positive bias when no selection correction is applied. The Heckman's predicted gap is 5.67% lower than the uncorrected one. There are no relevant differences in the predicted endowment contributions between the corrected and uncorrected estimations. The unexplained part of the gap decreases from 0.2135 to 0.1766. Adjusting the decomposition for selection bias further evidence the significant role of overtime as a widening factor of the gap[31].

Table 6. Heckman two-step estimation results

Predicted wages of males	8.1427***		
Predicted wages of females	7.7347***		
	Log scale		% points (€)
Total earnings gap	0.4080	***	50.38
	(0.070)		(0.105)
Explained part (E)	0.3794	***	46.14
	(0.031)		(0.046)
Unexplained part (U)	0.1766	***	19.32
	(0.070)		(0.084)
Interaction part (I)	-0.1480	***	-13.81
	(0.033)		(0.028)
Contribution to explained part:			
$\sum$ **Human capital controls**	**0.0187**	*	**1.89**
	(0.010)		(0.010)
$\sum$ **Demographic controls**	**-0.0010**		**-0.10**
	(0.002)		(0.002)
$\sum$ **Job controls**	**0.3401**	***	**40.50**
	(0.028)		(0.039)
$\sum$ **Overtime statuses**	**0.0216**	***	**2.19**
	(0.007)		(0.007)
$Weekly\ Overtime_{2016}$	0.0081		0.81
	(0.007)		(0.007)
$Weekly\ Overtime_{2015}$	-0.0003		-0.03
	(0.007)		(0.007)
$Weekly\ Overtime_{2014}$	0.0138	*	1.39
	(0.007)		(0.007)
N	1,133		

Note: Entries are gender differences in endowments multiplied by the correlative male coefficients. The deviation contrast transformation to dummy variables sets is applied to make the contribution of a categorical predictor to the unexplained part of the decomposition independent of the base category choice. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

[31] See Figure 6.A. for a visual comparison of the results obtained by the estimation of the three main models: Oaxaca – Blinder decomposition, pooled decomposition and Heckman correction.

5.3 Robustness check

I also explore whether the contribution of overtime to the gap is greater among a specific subsample, namely the most enlightened. Recent literature finds that the highest returns of overtime work are among the most educated workers in highly skilled occupations (Cortes & Pan, 2015). Analyses are then performed for a subsample of white collar workers[32]. By focusing on a more homogeneous group of individuals, this analysis can be considered as a robustness check to further control for unobserved heterogeneity. Table 4.A. presents the decomposition results. Four findings merit mention. Firstly, the estimated difference in monthly earnings among genders is higher than when considering the full sample. This does not come as a surprise. Women are less likely to perform senior managerial occupations than men (Holst & Friedrich, 2016). Also, the largest gaps are normally found in the financial and corporate sectors. Secondly, human capital controls contribute more to the gap among white collar workers in both decompositions. If white collar female workers had the same levels of education and experience as their male counterparts, their monthly wage would rise by around 4.5%. Thirdly, overtime continues explaining around 4% of the gap[33]. Despite this positive and both statistically and economically significant contribution of overtime to the gap among those performing professional or/and managerial work, there are no large differences with previous results. A possible explanation is that the fraction of workers in sectors in which working overtime hours is a common practice is low in the sample. Finally, the unexplained part of the gap accounts for the 19.83% of the gap according to the estimation results of the pooled decomposition (0.096/0.4840). The weight of the unexplained portion is 2.28% lower than in the full sample analysis under the same decomposition technic (19.83% versus 22.11%).

6 Concluding remarks

This paper seeks to answer the question of whether current monthly earnings gaps can be explained by current and past overtime statuses. Results suggest that the latter question is a coherent one to be asked.

[32] I refrain from performing the robustness check for the complementary subsample (i.e. blue collar workers) given sample size restrictions.
[33] Total overtime work accounts for the 4.59% (0.0222/0.4840) and for the 2.54% of the gap (0.0123/0.4840) in the Oaxaca – Blinder and the pooled decompositions, respectively.

This analysis is faced by applying two different decomposition technics, namely the Oaxaca – Blinder and the pooled decompositions. The former has been widely used in this literature which facilitates the comparison with previous studies. In this text a revised version is applied to control for overtime statuses. The pooled approach is an improved version of the Oaxaca – Blinder decomposition which allows for using a non-discriminatory price vector. It grants an econometric analysis which is closer to the reality as discrimination against one gender implies certain sort of favouritism towards the other. I find that the contribution of total overtime to the gender gap is positive and statistically significant in any of the decompositions. Its economic magnitude is not negligible either. Particularly, results of the Oaxaca-Blinder model suggest that current overtime work serve as a widening factor of the gap. The pooled decomposition finds that current and two-year lagged overtime statuses explains part of the gap. Importantly, the contribution of overtime statuses comes from differences in overtime means among genders, rather than from differences in prices or returns of overtime. In addition, the successive selection bias correction and robustness check further confirm previous results. Despite overtime work being the main focus of the analysis, the contribution of contracted hours as an explanatory factor of the gender gap cannot be neglected. Female monthly earnings fall behind male earnings due to the gap in working hours among both groups. All together this allows me to conclude that gender differences in working hours, both contracted and extraordinary, may be nowadays a leading explanation for the earnings differential.

My analysis speaks then to both labour and personnel economics. More importantly, it reconciles both fields. It examines the gender differences in earnings, a common topic in Labour Economics, from the perspective of Personnel Economics. This combination is possible by examining the monthly wage gap instead of the hourly wage gap, and by focussing on work flexibility and on the importance that work hour schedules have in the gap. This approach to study the gender gap in earnings is closer to the signalling theory or the theory of equalizing differences.

The extrapolation of the findings to the practice leaves a few implications. A wide gap in earnings among workers with comparable skills questions the competitiveness of the labour market. Even though, there is no evidence about different returns of overtime among workers, the disparities in working hours raise the alarm. Why do female workers contract less hours per week and work less overtime hours? The answer is not clear. However, what seems evident from the descriptive analysis of the data is that gender differences in ambition or career perspective are not the reason. In that case, the convergence in human capital investments would not exist. Goldin (2014) advocates for changing the structure of the jobs and their systems to reward or punish flexibility. On top of this, I propose to incentivize women to continue pursuing their careers and to invite men to support them in doing so.

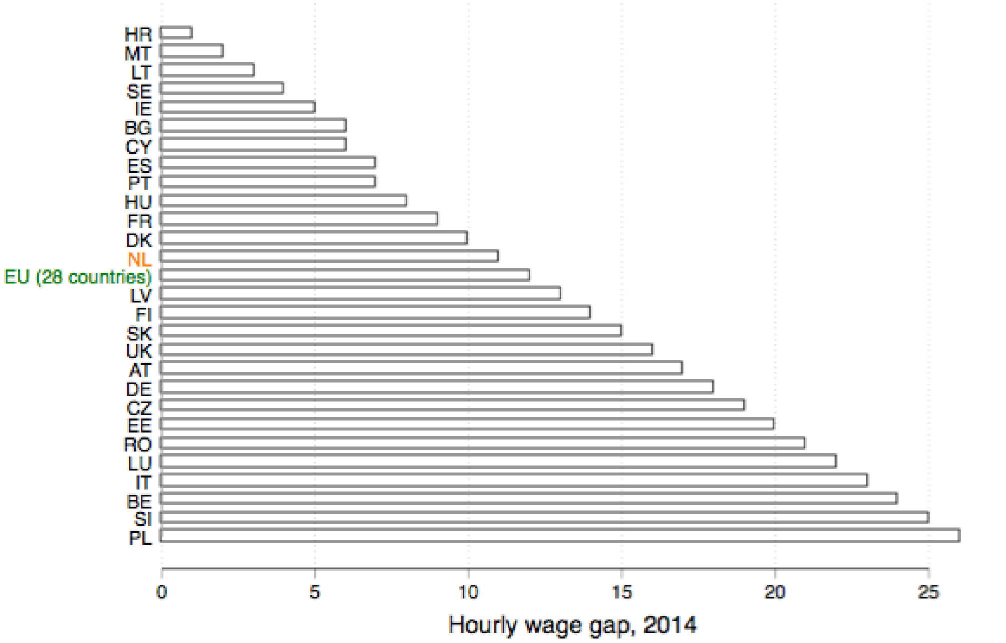
Finally, this analysis leaves room for further research. On the one hand, improvements can be done. It would be interesting to perform this analysis with a data set containing a higher fraction of workers in the corporate and financial spheres. In regard to the selection bias correction, the Heckman decomposition technic applied in this text has some drawbacks. It is a straightforward procedure to correct for selectivity bias, but there is no consensus on how the correction term should be tackled. It is probable that the potential possibilities to deal with this term come to slightly different results. Moreover, this correction imposes rather strong assumptions on the error terms.

Despite correcting for selection bias between those participating in the labour market and those who do not, one could argue that the endogeneity issue in overtime statuses is still latent. Workers with high wages, whether potential or effective, lose relatively more if they do not signal commitment and loyalty to the company and, as a consequence, work more hours than what the contract stipulates. Relatedly, it would be possible that women decide on their working hours based on the gender earnings differentials. The ultimate solution to this plausible reverse causation would be to find an appropriate exogenous determinant of working over hours.

On the other hand, this paper joins the many others which have implied that there are more potential explanations to the wage differential outside the human capital theory. Future research may contain the application of revisited decomposition technics and the examination of new factors. A promising field of study is open for future work.

Appendix

Figure 1.A. EU-28 gender hourly wage gap, 2014



Source: Eurostat
Note: Greek data is not available.

Table 1.A. Correlation table of the independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Overtime_{2016}$	1.00									
$Overtime_{2015}$	0.72***	1.00								
$Overtime_{2014}$	0.66***	0.70***	1.00							
% $Overtime_{2016}$	0.96***	0.67***	0.60***	1.00						
% $Overtime_{2015}$	0.46***	0.82***	0.51***	0.46***	1.00					
% $Overtime_{2014}$	0.53* **	0.66***	0.85***	0.51***	0.68***	1.00				
Experience	-0.04	-0.05	-0.04	-0.03	-0.01	-0.02	1.00			
Contracted hours/week	0.17***	0.17***	0.19**	0.05	0.06*	0.08***	-0.12***	1.00		
Company ownership	0.06*	0.09***	0.08***	0.02	0.05*	0.04	-0.07**	0.22***	1.00	
Job tenure	-0.08**	-0.06**	-0.07**	-0.06**	-0.02	-0.06**	0.57***	-0.04	-0.17***	1.00

Note: ***,** and * indicate significance at 1%, 5% and 10% respectively.

Figure 2. A. Distribution of (weekly) overtime by gender, mean

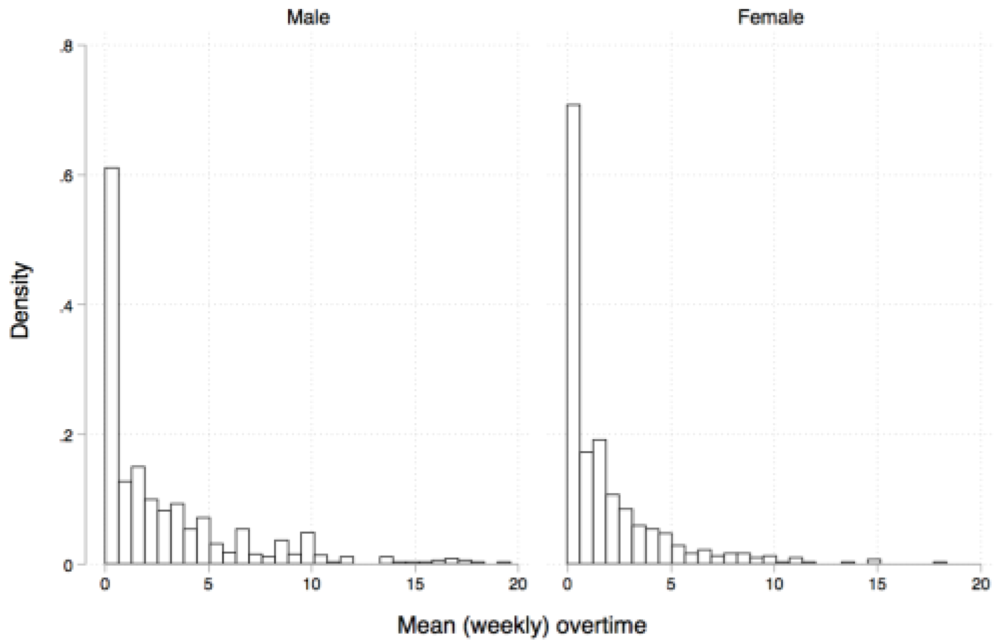


Figure 3. A. Distribution of (weekly) overtime by gender, year 2016

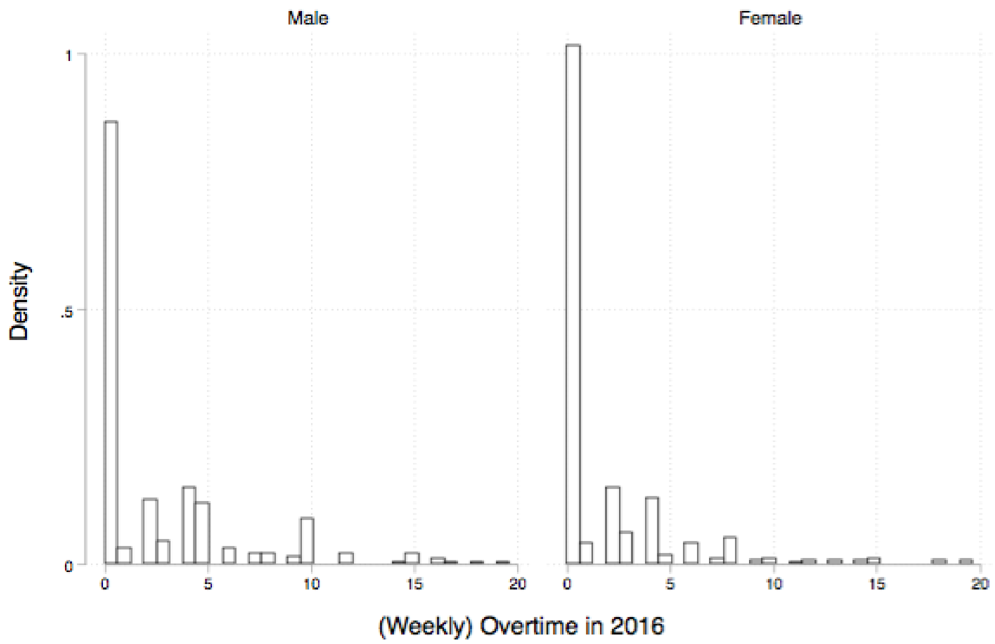


Figure 4. A. Distribution of (weekly) overtime by gender, year 2015

Figure 5. A. Distribution of (weekly) overtime by gender, year 2014

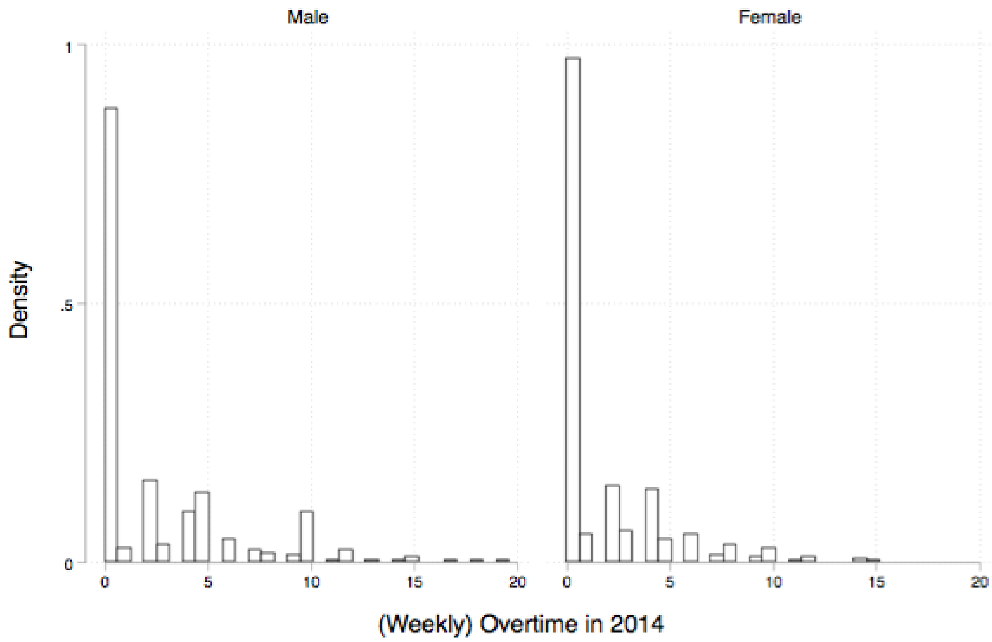


Table 2.A. Estimates of the log wage regressions

Dependent variable: ln (gross monthly income)			
	(1) Female	(2) Male	(3) Pooled
Female	–	–	-0.0984***
			(0.020)
Human capital controls			
Level of education [(a)]			
Intermediate secondary	-0.3422***	0.0577	-0.1682*
	(0.093)	(0.111)	(0.087)
Higher secondary	-0.1708	0.1667	0.0014
	(0.130)	(0.111)	(0 .090)
Intermediate vocational	-0.2798**	0.1273	-0.0780
	(0 .135)	(0.110)	(0.087)
Higher vocational	-0.0622	0.3182***	0.1356
	(0.131)	(0.112)	(0 .088)
University	0.1735	0.5145***	0.3621***
	(0.141)	(0.116)	(0.091)
Experience	0 .0237***	0.0198***	0.0201**
	(0.007)	(0.006)	(0.004)
Experience squared	-0.0002**	-0.0001	-0.0002**
	(0.000)	(0.000)	(0.000)
Demographic controls			
Origin [(b)]			
1st generation: western	-0.1514**	-0.1220**	-0.1165**
	(0.069)	(0.061)	(0.050)
1st generation: non western	-0.0126	-0.1638***	-0.1000***
	(0.075)	(0.050)	(0.038)
2nd generation: western	-0.0212	-0.0402	-0.0350
	(0.043)	(0.048)	(0.034)
2nd generation: non western	-0.0300	0.1618*	0.0703
	(0.072)	(0.097)	(0.055)
Job controls			
Contracted hours	0.0357***	0.0167***	0.0323***
	(0.002)	(0.004)	(0.001)
Private company	-0.0483	0.0018	-0.0319
	(0.032)	(0.038)	(0.025)
Job tenure	0.0025*	0.0018*	0.0021**
	(0.001)	(0.001)	(0.001)
Sector dummies	YES	YES	YES
Profession dummies	YES	YES	YES
Overtime statuses			
$Weekly\ Overtime_{2016}$	0.0069	0.0083**	0.0074***
	(0.007)	(0.004)	(0.003)
$Weekly\ Overtime_{2015}$	-0.0000	0.0001	0.0010
	(0.006)	(0.003)	(0.003)
$Weekly\ Overtime_{2014}$	0.0105**	0.0047	0.0059**
	(0.005)	(0.003)	(0.003)
Constant	6.6220***	6.8463***	6.4932***
	(0.1841)	(0.2104)	(0.152)
Adjusted R^2	0.7153	0.6228	0.7273
N	506	627	1,133

Note: Robust standard errors in parentheses. * significant at 10% level, ** significant at 5% level, *** significant at 1% level. [(a)] Base category: primary school. [(b)] Base category: Dutch.

Table 3.A. First and second stage of the Heckman correction method

First stage Dependent variable: Participation in paid work	
Civil status [(a)]	
Separated	-0.7062
	(0.599)
Divorced	-0.1763
	(0.166)
Widow	-0.6909***
	(0.259)
Never been married	-0.0806
	(0.153)
# of children in the household	
One child	0.3167***
	(0.110)
Two children	0.4098***
	(0.101)
Three children	0.5314***
	(0.155)
Four children	-0.3571
	(0.351)
Five children	0.3297
	(0.628)
Position within the household [(c)]	
Wedded partner	-0.5518***
	(0.140)
Other	-0.2848**
	(0.133)
Constant	0.0601
	(0.132)
Rho	-0.1622
Sigma	0.2636
Second stage Dependent variable: ln(gross monthly income)	
Human capital controls	YES
Demographic controls	YES
Job controls	YES
$Weekly\ Overtime_{2016}$	0.0066
	(0.005)
$Weekly\ Overtime_{2015}$	-0.0002
	(0.006)
$Weekly\ Overtime_{2014}$	0.0106**
	(0.005)
Mills	
λ	-0.0428
	(0.075)
Wald Chi2	1214.05
Prob > chi2	0.000
Censored observations	647
Uncensored observations	506
N	1,153

Note: * significant at 10% level, ** significant at 5% level, *** significant at 1% level. [(a)] Base category: married. [(b)] Base category: Self-owned dwelling. [(c)] Base category: Household head.

Figure 6.A. Oaxaca – Blinder, pooled and Heckman decompositions of the monthly earnings gap, 2016

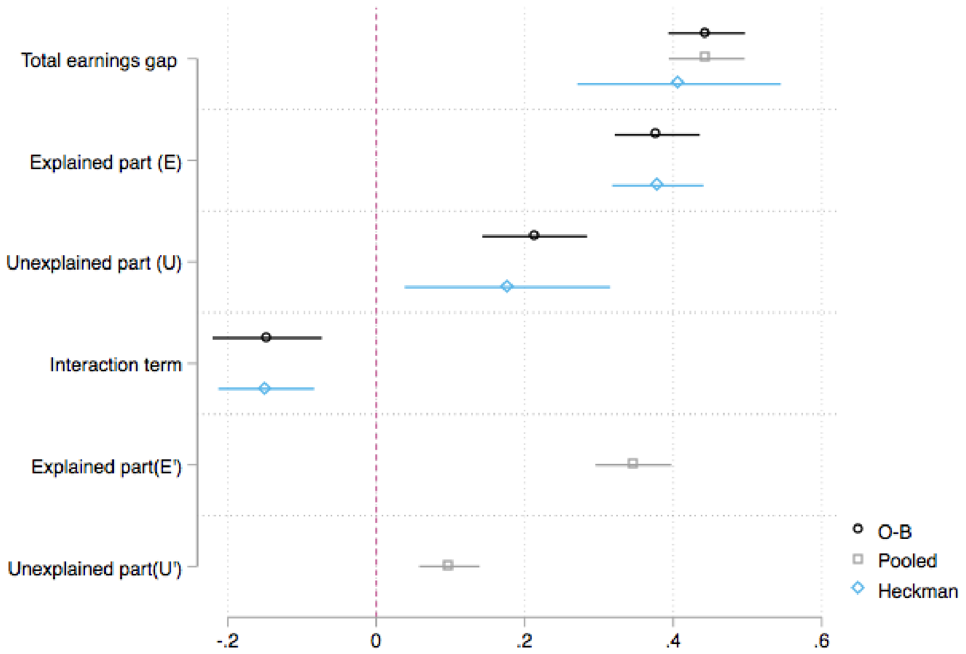


Table 4.A. Decompositions of the monthly earnings gap for the subsample of white-collar workers

	Oaxaca-Blinder decomposition			Pooled decomposition		
Predicted wages of males	8.2177 ***			8.2177 ***		
Predicted wages of females	7.7337***			7.7337***		
	Log scale		% points (€)	Log scale		% points (€)
Total wage gap	0.4840	***	62.26	0.4840	***	62.26
	(0.026)		(0.041)	(0.026)		(0.041)
Explained part (E)	0.4089	***	50.52	0.3881	***	47.41
	(0.027)		(0.042)	(0.026)		(0.038)
Unexplained part (U)	0.1996	***	22.09	0.0960	***	10.07
	(0.038)		(0.048)	(0.021)		(0.023)
Interaction term (I)	-0.1245	***	-11.71			
	(0.039)		(0.035)			
Contribution to explained part:						
∑ Human capital controls	**0 .0435**	***	**4.45**	**0.0440**	***	**4.5**
	(0.011)		(0.012)	(0.011)		(0.012)
∑ Demographic controls	**0.0003**		**0.03**	**-0.0008**		**-0.08**
	(0.002)		(0.002)	(0.002)		(0.002)
∑ Job controls	**0.3430**	***	**40.92**	**0.3324**	***	**39.44**
	(0.023)		(0.033)	(0.022)		(0.030)
∑ Overtime percentages	**0.0222**	***	**2.24**	**0.0123**	***	**1.24**
	(0.008)		(0.008)	(0.004)		(0.006)
% $Weekly\ Overtime_{2016}$	0.0011		0.11	0.0037		0.38
	(0.008)		(0.008)	(0.003)		(0.003)
% $Weekly\ Overtime_{2015}$	0.0064		0.64	0.0032		0.32
	(0.008)		(0.007)	(0.005)		(0.003)
% $Weekly\ Overtime_{2014}$	0.0147	*	1.48	0.0054	*	0.55
	(0.008)		(0.008)	(0.003)		(0.003)
N	972			972		

Note: Entries are gender differences in endowments multiplied by the correlative male/pooled coefficients. Robust standard errors in parentheses. The deviation contrast transformation to dummy variables sets is applied to make the contribution of a categorical predictor to the unexplained part of the decomposition independent of the base category choice. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

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